A Convolutional Transformer-based Model for Estimation of Soiling-driven PV Power Loss

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***Abstract*—Using a well-built estimation model, one effective way of diagnosing PV systems is to compare the estimated PV power output and the true PV power output. Considering that PV power output is affected by various external factors, we first need to build a reliable model for PV power output estimation. In this paper, we propose a model using a convolutional transformer for the estimation of PV power loss by soiling effects. The input to the model is an RGB image and the output is the estimated power loss class. Using the five power loss classes, through experiments, we show that our model achieves 83.37% classification accuracy.**

***Index Terms*—PV power loss, soiling effect, deep learning, transformer, computer vision.**

I. Introduction

As one of the renewable energy technologies, photovoltaic (PV) systems is widely used. Their share is increasing in the energy and power mix worldwide [1]. Considering that the share of PV systems in the power mix is not negligible, operating PV systems in stable conditions is quite important.

One simple approach for the stable operation of PV systems is to conduct an estimation of PV power output and compare the estimated PV power output and the true PV power output [2]. Assuming that the estimation model is well built, a large gap between the estimation and the true value may indicate out of order of PV systems.

For the reliable comparison-based diagnosis, we must keep in mind that PV power output is affected by various external factors such as snow, clouds, soil, and so on [3]. In other words, we need to be able to estimate PV power output by considering external factors. In particular, in Korea, yellow dust and pollen cover the surface of PV panels in spring, hindering power generation.

To this end, in this paper. we propose a deep learning model to estimate PV power loss by the soiling effect. Assuming that the RGB image of a target PV system is given, we build a model using a convolutional transformer [4]. Given an RGB image, our model estimates the PV power loss class. Our research uses five power loss classes (i.e., five classes evenly divided from 0.2 to 1.0 as the loss ratio). Through the experiments using the data of [3], our model achieves 83.37% classification accuracy. We also examine the R2 score between the true loss ratio and the predicted loss ratio in terms of the regression perspective. Our model shows a 0.7388 R2 score.

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The rest of this paper is organized as follows. Section II describes our model for PV power loss class estimation. Section III introduces the experimental results. Section IV concludes this paper.

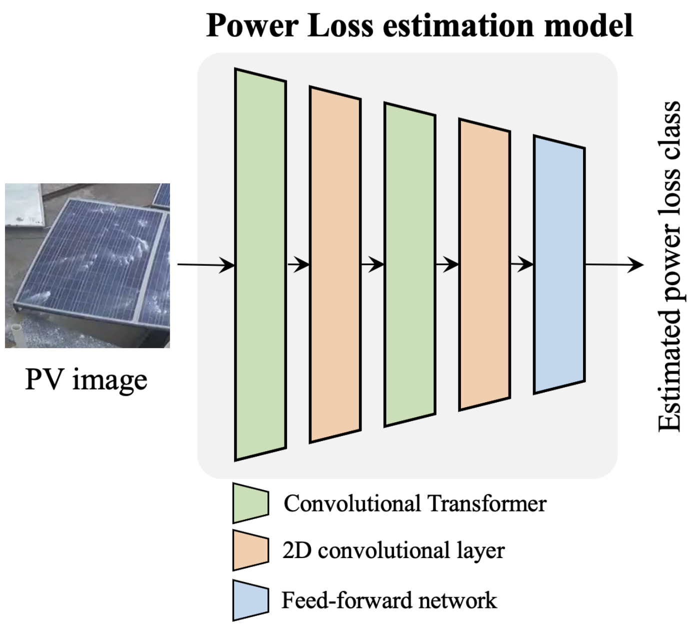
II. PV Power Loss Estimation Model

Fig. 1(a) shows our proposed model for the PV power loss class estimation. The input to the model is an RGB image and the output is the estimated power loss class. The proposed model includes the convolutional transformer, 2D convolutional layer, and feed-forward network.

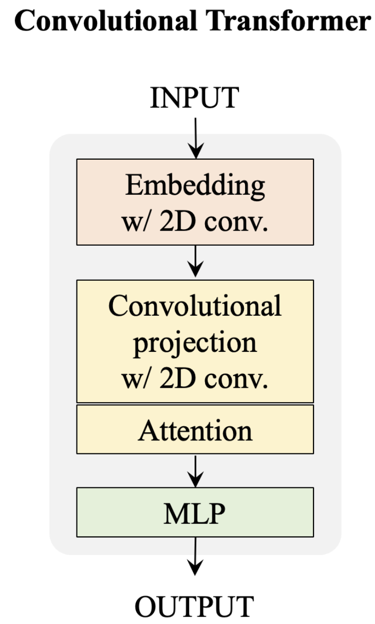
As a main block of the proposed model, we first describe the convolutional transformer. Following the concept of vision transformer [5], the convolutional transformer enhances the performance by introducing convolutional token embedding and convolutional projection for attention. The convolutional token embedding performs a downsample and then a flattening operation. Through the downsampling, the feature map size decreases while increasing the number of channels. In other words, the convolutional transformer can leverage the hierarchical structure of a typical CNN architecture through downsampling. The convolutional transformer replaces a flattening operation with a depth-wise convolutional operation in converting the input value to Q, K, and V to be used for attention operation. The detailed architecture of the convolutional transformer is depicted in Fig. 1(b).

The 2D convolutional layer of Fig. 1(a) reduces the dimension of the output of the convolutional transformer further. The feed-forward network of Fig. 1(a) sequentially reduces the dimension of the output of the last convolutional transformer to produce an estimated loss class.

Regarding the application of the proposed RGB image-based method to the real environment, assuming that PV panels are exposed to a similar environment, it can be applied to many PV panels only with images of representative panels among geographically close panels.

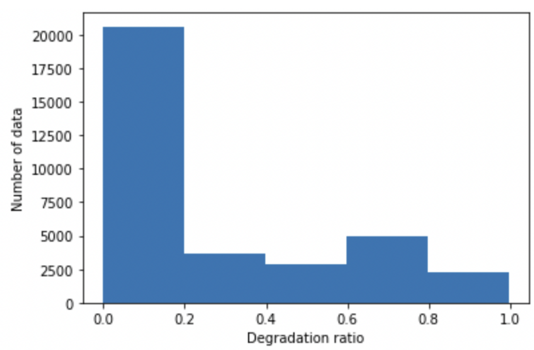


(a) An overview of the proposed model.

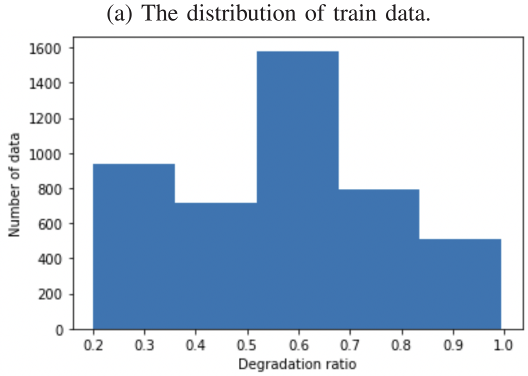


(b) Convolutional Transformer.

Fig. 1: Proposed model.



(a) The distribution of train data.



(b) The distribution of the filtered test data.

Fig. 2: The distribution of train and test data.

III. Experimental Study

A. Data

For the experiments, we use PV panel soiling image dataset [6]. The dataset includes 45,754 images of PV panels with power loss labels. Using the two PV panels, soiling experiments were conducted on the first panel (captured by the camera) while the other panel was used for reference. Images were captured every 5 seconds and power generated by the panels was recorded. The soiling impact is reported as the percentage power loss concerning the reference panel.

B. Implementation

We implement our model using Pytorch of version 1.13 [7]. The model is trained using an Adam optimizer with a learning rate of 1E-5. We divide the whole dataset into train data (34,316) and test data (11,438). A model is trained with the train data. For the test phase, we filter the test data by ignoring the data whose true loss ratio is less than 0.2 to focus on high-loss cases. In this case, the number of the filtered test data is 4,535. Fig. 2 shows the class distribution of the train and test data. In terms of the power loss ratio, we use five classes evenly divided from 0.2 to 1.0. The original dataset includes images of 192 x 192 x 3. We resize the images into 128 x 128 x 3 to reduce the implementation overhead.

C. Results

Among 4,535 test data, the classes of 3,781 test data are correctly classified, so resulting in a classification accuracy of 83.37%. Table I shows the classification accuracy in detail. The rows indicate the true power loss classes and the columns indicate the predicted power loss classes. Fig. 3 shows the relationship between the true loss and the predicted loss in terms of the regression perspective. One observation is that each class shows different accuracy. In particular, class 1 (0.20 $\sim$ 0.36) and class 3 (0.52 $\sim$ 0.68) show classification accuracy

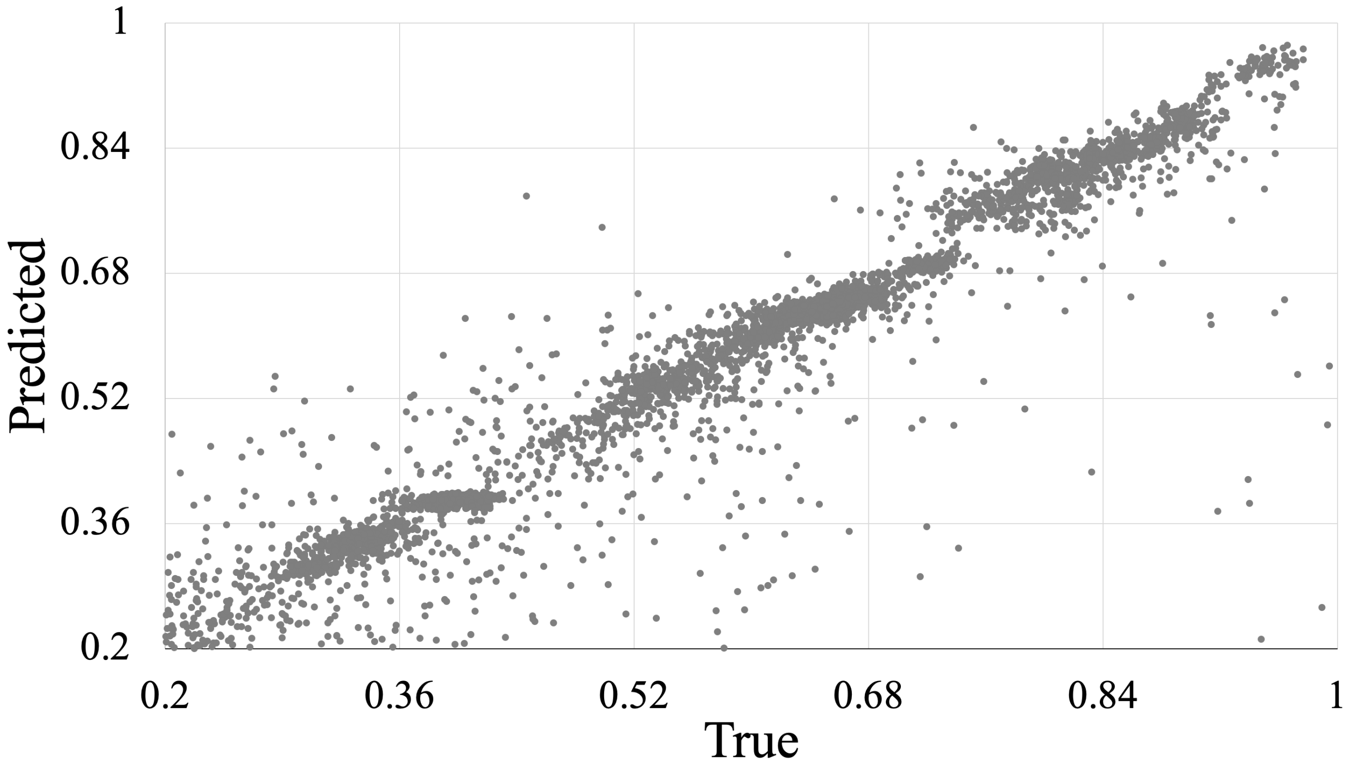


Fig. 3: True loss vs. Predicted loss (in terms of the regression perspective).

TABLE I: Classification accuracy in detail.

		Predicted class					Total	Accuracy (in %)
		1	2	3	4	5		
True class	1 (0.20 ∼ 0.36)	890 (correct)	51	3	0		944	94.27
	2 (0.36 ∼ 0.62)	177	492 (correct)	52	2	0	723	68.04
	3 (0.52 ∼ 0.68)	58	91	1,441 (correct)	3	0	1,593	90.45
	4 (0.68 ∼ 0.84)	12	5	131	628 (correct)	21	788	79.69
	5 (0.84 ∼ 1.00)	11	4	7	135	330 (correct)	487	67.76
	Total	3,781 (correct)					4,535	83.37

higher than 90%. On the contrary, class 2 (0.36 ∼ 0.62) and class 5 (0.84 ∼ 1.00) shows the classification accuracy lower than 70%. Considering that the proposed model is based on RGB images, the results show that some images (of class 2 and 5, particularly) may not be enough to convey information for estimation. Fig. 3 shows the strong relationship between the true loss ratio and the predicted loss ratio. The R2 score between the true loss ratio and the predicted loss ratio is 0.738 which can be seen as showing a high level of correlation.

IV. Conclusion

To accurately diagnose PV systems, it is necessary to understand how external factors affect the amount of PV power output. In this paper, we study a way for estimating PV power loss by soiling factors. In particular, we try to build a model with only RGB images of PV panels. As future work, we plan to consider additional weather conditions including irradiance which is commonly measured together with PV power output. We also plan to consider other external factors like snow, bird poop, and so on.

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